MVA ASSIGNMENT 6

MEMBER INFORMATION

Ruixin Yang (RUID: 197000459)

Aishwarya Senthilvel (RUID: 199001269)

FACTOR ANALYSIS

Factor analysis is a way to condense the data from many variables into just a few variables. For this reason, it is also sometimes called "dimension reduction." We can reduce the "dimensions" of the data into one or more "super-variables." The most common technique is known as Principal Component **Analysis** (PCA).

Since the dataset contains categorical variables, we are using dummy variables to replace categorical variables and drop intercepts.

The below code was used to perform the same:

```
# Using dummy variables to replace categorical variables and drop intercepts
job<- model.matrix(~job, data = Bank)[,-1]
marital = model.matrix(~marital, data = Bank)[,-1]
education = model.matrix(~education, data = Bank)[,-1]
default = model.matrix(~default, data = Bank)[,-1]
housing = model.matrix(~housing, data = Bank)[,-1]
loan = model.matrix(~loan, data = Bank)[,-1]
contact = model.matrix(~contact, data = Bank)[,-1]
month = model.matrix(~month, data = Bank)[,-1]
poutcome = model.matrix(~poutcome, data = Bank)[,-1]
Bank_new = cbind(Bank$age, job,marital,education,default, Bank$balance, housing,loan,contact, Bank$day, month, Bank[,12:15],poutcome)
```

CORRELATION MATRIX

```
# Computing Correlation Matrix
corrm.bank <- cor(Bank_new)
corrm.bank
plot(corrm.bank)
Bank_pca <- prcomp(Bank_new[-1], scale=TRUE)
summary(Bank_pca)
plot(euroemp_pca)
```

EIGEN VALUES

A table containing eigenvalues and %'s accounted, follows. Eigenvalues are the sdev^2

```
> # A table containing eigenvalues and %'s accounted, follows. Eigenvalues are the sdev^2
> (eigen_bank <- round(Bank_pca$sdev^2,2))
 [1] 3.15 2.67 2.03 1.92 1.65 1.44 1.40 1.27 1.23 1.21 1.15 1.14 1.12 1.09 1.07 1.04 1.03 1.03 1.01
[20] 0.99 0.98 0.95 0.93 0.90 0.88 0.86 0.83 0.82 0.77 0.77 0.63 0.60 0.56 0.49 0.45 0.26 0.23 0.18
[39] 0.11 0.09 0.07
> names(eigen_bank) <- paste("PC",1:9,sep="")
> eigen_bank
  PC1   PC2   PC3   PC4   PC5   PC6   PC7   PC8   PC9 <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
3.15  2.67  2.03  1.92  1.65  1.44  1.40  1.27  1.23  1.21  1.15  1.14  1.12  1.09  1.07  1.04  1.03  1.03  1.01  0.99
<NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
0.98  0.95  0.93  0.90  0.88  0.86  0.83  0.82  0.77  0.77  0.63  0.60  0.56  0.49  0.45  0.26  0.23  0.18  0.11  0.09
<NA>
0.07
```

```
> sumlambdas <- sum(eigen_bank)
> sumlambdas
[1] 41
```

```
> propvar <- round(eigen_bank/sumlambdas,2)
> propvar
  PC1   PC2   PC3   PC4   PC5   PC6   PC7   PC8   PC9 <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
0.08  0.07  0.05  0.05  0.04  0.04  0.03  0.03  0.03  0.03  0.03  0.03  0.03  0.03  0.03  0.03  0.03  0.03  0.02  0.02
<NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
0.02  0.02  0.02  0.02  0.02  0.02  0.02  0.02  0.02  0.02  0.02  0.01  0.01  0.01  0.01  0.01  0.01  0.00  0.00  0.00
<NA>
0.00
```

CUMULATIVE SUM

Returns a vector whose elements are the cumulative sums, products, minima or maxima of the elements of the argument.

```
> cumvar_bank <- cumsum(propvar)
> cumvar_bank
  PC1   PC2   PC3   PC4   PC5   PC6   PC7   PC8   PC9 <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
0.08  0.15  0.20  0.25  0.29  0.33  0.36  0.39  0.42  0.45  0.48  0.51  0.54  0.57  0.60  0.63  0.66  0.69  0.71  0.73
<NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
0.75  0.77  0.79  0.81  0.83  0.85  0.87  0.89  0.91  0.93  0.95  0.96  0.97  0.98  0.99  1.00  1.01  1.01  1.01  1.01
<NA>
1.01
```

ROW BIND

The rbind() function combines vector, matrix or data frame by rows

```
> matlambdas <- rbind(eigen_bank,propvar,cumvar_bank)
> matlambdas
             PC1  PC2  PC3  PC4  PC5  PC6  PC7  PC8  PC9 <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
eigen_bank  3.15 2.67 2.03 1.92 1.65 1.44 1.40 1.27 1.23 1.21 1.15 1.14 1.12 1.09 1.07 1.04 1.03
propvar     0.08 0.07 0.05 0.05 0.04 0.04 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03
cumvar_bank 0.08 0.15 0.20 0.25 0.29 0.33 0.36 0.39 0.42 0.45 0.48 0.51 0.54 0.57 0.60 0.63 0.66
            <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA> <NA>
eigen_bank  1.03 1.01 0.99 0.98 0.95 0.93 0.90 0.88 0.86 0.83 0.82 0.77 0.77 0.63 0.60 0.56 0.49
propvar     0.03 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.01 0.01 0.01
cumvar_bank 0.69 0.71 0.73 0.75 0.77 0.79 0.81 0.83 0.85 0.87 0.89 0.91 0.93 0.95 0.96 0.97 0.98
            <NA> <NA> <NA> <NA> <NA> <NA> <NA>
eigen_bank  0.45 0.26 0.23 0.18 0.11 0.09 0.07
propvar     0.01 0.01 0.01 0.00 0.00 0.00 0.00
cumvar_bank 0.99 1.00 1.01 1.01 1.01 1.01 1.01
```

```
> # Multiplying each column of the eigenvector's matrix by the square-root of the corresponding
 eigenvalue in order to get the factor loadings
> unrot.fact.bank <- sweep(pcafactors.bank,MARGIN=2,Bank_pca$sdev[1:4],`*`)
> unrot.fact.bank
                           PC1         PC2          PC3          PC4
jobblue-collar      0.14951274 -0.43780067  0.009571505 -0.1795763778
jobentrepreneur     0.02058937  0.03217522 -0.021353068 -0.1470652850
jobhousemaid        0.01636437  0.07109852 -0.110197233 -0.0930008559
jobmanagement      -0.15395780  0.56947848  0.417123716 -0.2213804428
jobretired         -0.02860968  0.05814980 -0.288245825 -0.1312632133
jobself-employed    0.02335733  0.05757946  0.029569349 -0.0717194692
jobservices         0.09031330 -0.25095535 -0.082745030  0.1940669483
jobstudent         -0.09111957  0.04956159  0.039870552  0.3102150359
jobtechnician      -0.01466178 -0.01040693 -0.102052319  0.3261952797
jobunemployed      -0.01498937  0.01171090 -0.060209585  0.0425874146
jobunknown         -0.01311524  0.07261488 -0.080805048 -0.0576647138
maritalmarried      0.11829597 -0.14825619 -0.344601485 -0.7786582944
maritalsingle      -0.14029417  0.15723862  0.348380888  0.7854346120
educationsecondary  0.13320243 -0.57723891 -0.386073354  0.3708444777
educationtertiary  -0.20387800  0.69379338  0.453183950 -0.1734139672
educationunknown   -0.01163646  0.01330453  0.017469644 -0.0741352427
default             0.05419029 -0.02024681 -0.007948203  0.0704504937
Bank$balance       -0.08480647  0.14261830  0.046468706 -0.1251062453
housing             0.04600216 -0.50475005  0.345921956 -0.0860119854
loan                0.09144342 -0.06095888 -0.169821168  0.0069523064
contacttelephone   -0.09719851  0.07187004 -0.322966540 -0.0314540699
contactunknown      0.47942086 -0.37015539  0.503625990 -0.1480258539
Bank$day            0.06989414  0.12888848 -0.215834205  0.0969182385
monthaug            0.03045409  0.41943652 -0.194871209  0.0618169682
monthdec           -0.13926162  0.01657705 -0.020642333  0.0151880307
monthfeb           -0.16572888  0.03929104 -0.021355638  0.0654239384
monthjan           -0.16384492  0.05240020 -0.131378365  0.0899661167
```

monthjul	0.16532959	0.14631727	-0.438412776	0.0966020034
monthjun	0.23959665	-0.01736153	0.253686503	-0.1558497483
monthmar	-0.07672131	0.06968513	-0.064160697	-0.0002510915
monthmay	0.10032556	-0.55226957	0.478896042	-0.0344113900
monthnov	-0.14958452	0.11813374	-0.079707734	-0.0900422308
monthoct	-0.14641786	0.06428176	-0.087136599	-0.0349177771
monthsep	-0.14487865	0.04394884	0.013989055	0.0188836065
duration	-0.03302211	-0.04917935	0.012901010	0.0396986209
campaign	0.16606829	0.13983036	-0.100676278	0.0091389167
pdays	-0.80915432	-0.29356519	0.042864912	-0.0787042286
previous	-0.74783399	-0.21029882	0.013282385	-0.0623660628
poutcomeother	-0.52173002	-0.16269610	0.040580538	-0.0348454425
poutcomesuccess	-0.39353773	-0.02339674	-0.097036438	-0.0289411027
poutcomeunknown	0.90183566	0.24434178	0.002725079	0.0798714668

FACTOR ANALYSIS

First, we do the principal component analysis to our dataset after we transformed all categorical variables to dummy variables. And we therefore extract the matrix that contains contributions from variables to components. Then we chose the first four columns since their variances are relatively large. Then we multiplied each column of the eigenvector's matrix by the square-root of the corresponding eigenvalue to get the factor loadings. They are the first four columns in the table in the appendix.

After that, we computed the communalities. The result is the fifth column in the table of the appendix. Then we performed the varimax rotation and get the loadings of factors. It is an alternative method to get loads. And it can preserve the orthogonality of factors. They are the 6th to 9th columns in the table in appendix.

Then we computed scores of rotated factors. Then we started to detect potential cross-loadings. The result is the following.

```
Principal Components Analysis
Call: principal(r = bank_new, nfactors = 4, rotate = "varimax")
Standardized loadings (pattern matrix) based upon correlation matrix
                  RC1   RC2   RC4   RC3     h2   u2 com
bank$age         0.03 -0.02  0.22  0.72 0.5631 0.44 1.2
jobblue-collar  -0.06  0.28 -0.37  0.14 0.2355 0.76 2.3
jobentrepreneur  -0.02 -0.06 -0.01  0.09 0.0126 0.99 1.8
jobhousemaid     -0.02 -0.02  0.10  0.14 0.0294 0.97 1.9
```

```
jobmanagement       0.02 -0.75  0.03 -0.08 0.5702 0.43 1.0
jobretired          0.05  0.06  0.24  0.41 0.2369 0.76 1.7
jobself-employed   -0.03 -0.08 -0.01  0.03 0.0086 0.99 1.8
jobservices        -0.04  0.31 -0.06 -0.11 0.1155 0.88 1.4
jobstudent          0.06  0.03  0.09 -0.30 0.1017 0.90 1.3
jobtechnician       0.01  0.17  0.16 -0.22 0.1047 0.90 2.8
jobunemployed       0.01  0.04  0.06 -0.02 0.0056 0.99 1.9
jobunknown          0.01 -0.03  0.09  0.10 0.0187 0.98 2.2
maritalmarried     -0.04  0.06 -0.10  0.76 0.5856 0.41 1.0
maritalsingle       0.05 -0.07  0.09 -0.82 0.6813 0.32 1.0
educationsecondary -0.01  0.79 -0.02 -0.12 0.6389 0.36 1.0
educationtertiary   0.04 -0.85  0.10 -0.15 0.7641 0.24 1.1
educationunknown    0.01 -0.05 -0.02  0.12 0.0165 0.98 1.5
default            -0.05  0.05  0.01 -0.05 0.0085 0.99 3.0
bank$balance        0.06 -0.19  0.04  0.12 0.0549 0.95 2.0
housing             0.03  0.16 -0.61 -0.10 0.4035 0.60 1.2
loan               -0.07  0.16  0.06  0.01 0.0358 0.96 1.7
contacttelephone    0.10  0.10  0.28  0.18 0.1315 0.87 2.3
contactunknown     -0.41  0.01 -0.67  0.07 0.6261 0.37 1.7
bank$day           -0.09  0.08  0.25 -0.07 0.0809 0.92 1.7
monthaug           -0.10 -0.17  0.42 -0.01 0.2179 0.78 1.4
monthdec            0.13 -0.02  0.04  0.00 0.0203 0.98 1.3
monthfeb            0.15 -0.02  0.08 -0.04 0.0317 0.97 1.7
monthjan            0.15  0.04  0.17 -0.05 0.0556 0.94 2.3
monthjul           -0.18  0.21  0.40  0.00 0.2330 0.77 1.9
monthjun           -0.23 -0.15 -0.25  0.14 0.1584 0.84 3.2
monthmar            0.07 -0.03  0.10  0.05 0.0185 0.98 2.5
monthmay           -0.01  0.14 -0.71 -0.09 0.5250 0.48 1.1
monthnov            0.13 -0.09  0.12  0.04 0.0407 0.96 3.1
monthoct            0.14 -0.04  0.11  0.09 0.0414 0.96 2.8
monthsep            0.13 -0.06  0.04 -0.03 0.0231 0.98 1.7
duration            0.04  0.04 -0.02 -0.02 0.0041 1.00 3.3
campaign           -0.19 -0.01  0.14 -0.01 0.0553 0.94 1.9
pdays               0.85  0.03 -0.16  0.00 0.7481 0.25 1.1
previous            0.77  0.00 -0.09  0.00 0.6072 0.39 1.0
poutcomeother       0.54  0.00 -0.09 -0.04 0.3016 0.70 1.1
poutcomesuccess     0.40 -0.01  0.09  0.06 0.1696 0.83 1.1
poutcomeunknown    -0.93  0.00  0.09 -0.01 0.8791 0.12 1.0

                   RC1  RC2  RC4  RC3
```

```
SS loadings           3.12 2.39 2.34 2.31
Proportion Var         0.07 0.06 0.06 0.05
Cumulative Var         0.07 0.13 0.19 0.24
Proportion Explained  0.31 0.24 0.23 0.23
Cumulative Proportion 0.31 0.54 0.77 1.00

Mean item complexity =  1.8
Test of the hypothesis that 4 components are sufficient.

The root mean square of the residuals (RMSR) is  0.06
 with the empirical chi square  25145.71  with prob <  0

Fit based upon off diagonal values = 0.68
```

As you can see, many variables are problematic. That means we need to revise our specification. Then we got eigenvalues of PCA above. Here is the result.

[1] 3.146 2.685 2.348 1.981 1.672 1.443 1.401 1.277 1.251 1.217 1.155 1.144 1.140 1.119 1.072 1.042

[17] 1.032 1.028 1.018 0.993 0.979 0.969 0.940 0.904 0.883 0.861 0.833 0.819 0.775 0.769 0.625 0.597

[33] 0.557 0.494 0.458 0.446 0.262 0.214 0.173 0.113 0.094 0.070

Then we computed the standardized loadings of factors from the analysis above. Here is the outcome.

```
Loadings:
                 RC1    RC2    RC4    RC3
bank$age                       0.218  0.717
jobblue-collar           0.279 -0.366  0.144
jobentrepreneur
jobhousemaid                           0.138
jobmanagement           -0.750
jobretired                0.243  0.414
jobself-employed
jobservices              0.312        -0.112
jobstudent                            -0.297
jobtechnician            0.174  0.158 -0.222
jobunemployed
jobunknown
maritalmarried                         0.756
```

```
maritalsingle                -0.816
educationsecondary    0.790  -0.122
educationtertiary    -0.854  0.100 -0.154
educationunknown                0.116
default
bank$balance         -0.190  0.116
housing               0.155 -0.607
loan                  0.162
contacttelephone      0.103  0.104  0.281  0.176
contactunknown       -0.414  -0.671
bank$day                      0.248
monthaug             -0.104 -0.169  0.422
monthdec              0.134
monthfeb              0.154
monthjan              0.153  0.167
monthjul             -0.175  0.208  0.399
monthjun             -0.233 -0.153 -0.250  0.135
monthmar                      0.102
monthmay                0.137 -0.705
monthnov              0.129  0.117
monthoct              0.139  0.113
monthsep              0.132
duration
campaign             -0.187  0.141
pdays                 0.849  -0.161
previous              0.774
poutcomeother         0.540
poutcomesuccess       0.398
poutcomeunknown      -0.933

                 RC1   RC2   RC4   RC3
SS loadings    3.122 2.389 2.343 2.307
Proportion Var 0.074 0.057 0.056 0.055
```

Then we extracted the communality from the analysis above. Here is the outcome.

bank$age jobblue-collar jobentrepreneur jobhousemaid jobmanagement

0.563059202 0.235513491 0.012594334 0.029409786 0.570159883

jobretired jobself-employed jobservices jobstudent jobtechnician

0.236856931 0.008604994 0.115475768 0.101717518 0.104721857

jobunemployed jobunknown maritalmarried maritalsingle educationsecondary

0.005643796 0.018688175 0.585578991 0.681257997 0.638941229

educationtertiary educationunknown default bank$balance housing

0.764123544 0.016472437 0.008538247 0.054889830 0.403470239

loan contacttelephone contactunknown bank$day monthaug

0.035832464 0.131538660 0.626090035 0.080852145 0.217851796

monthdec monthfeb monthjan monthjul monthjun

0.020344847 0.031693621 0.055607644 0.232981703 0.158401831

monthmar monthmay monthnov monthoct monthsep

0.018531438 0.524992245 0.040699789 0.041356430 0.023071487

duration campaign pdays previous poutcomeother

0.004078663 0.055291726 0.748138634 0.607216429 0.301593662

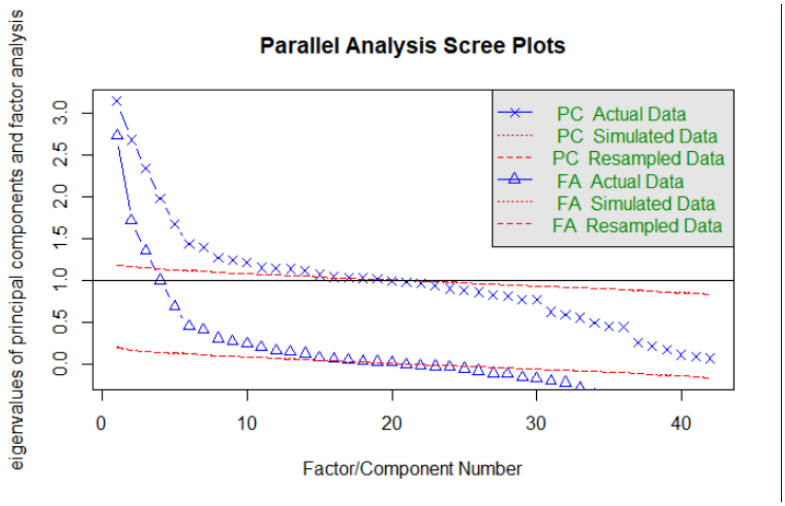
poutcomesuccess poutcomeunknown

0.169593595 0.879075148

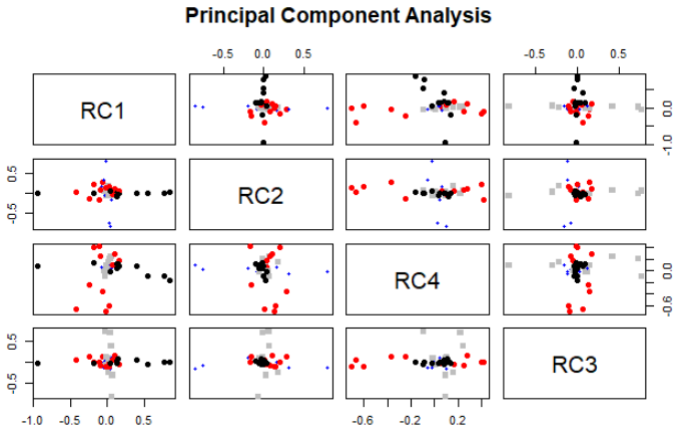
Finally, we also got scores from the analysis above.

FA UTILITIES

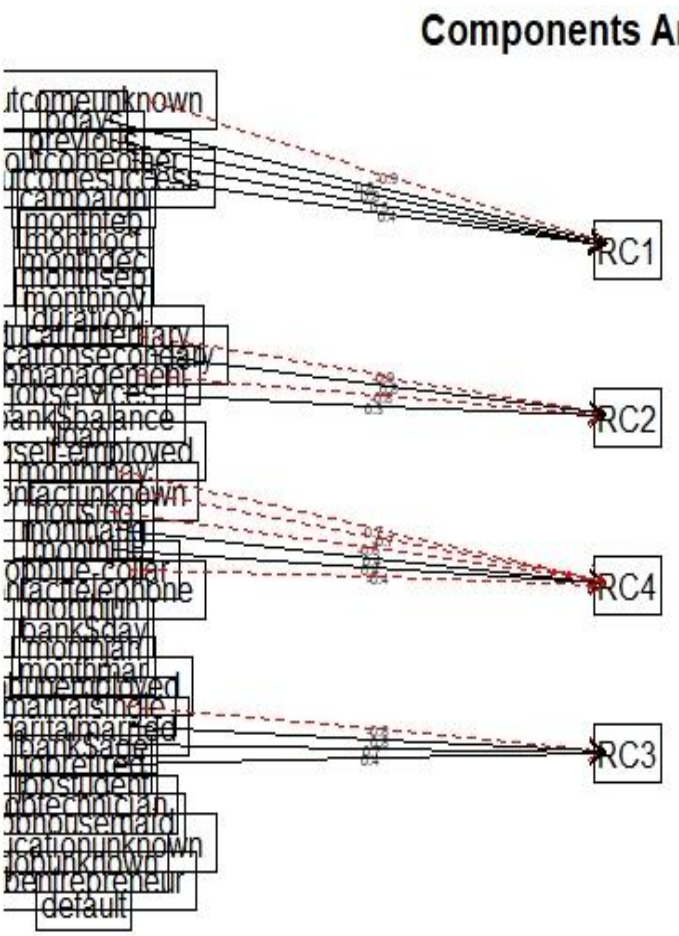
First, we apply the fa.parallel function to our dataset to find out the recommended number of factors. Here is the outcome.



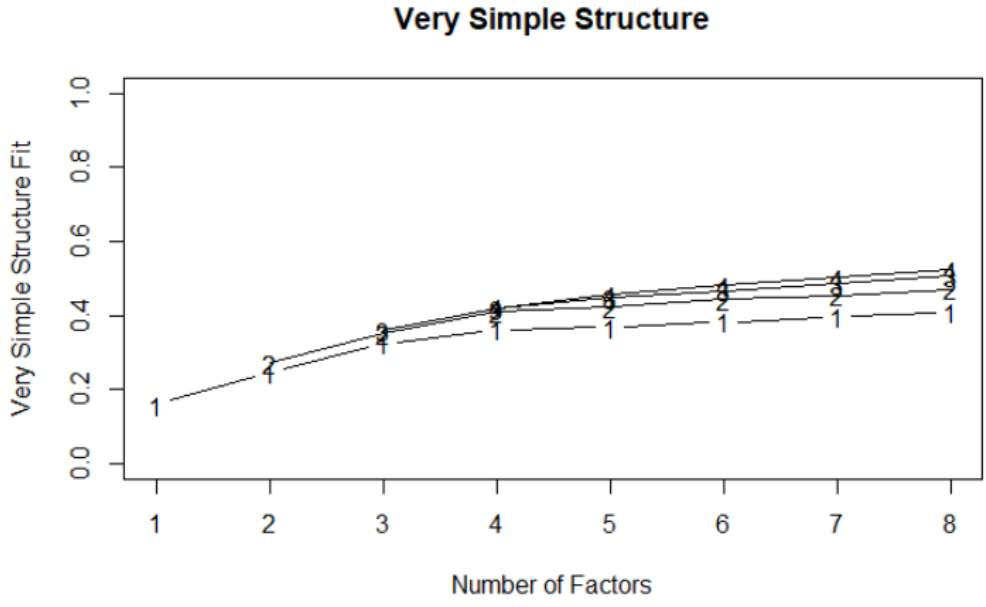
We can see that FA actual data recommends four factors. That is our choice.Then we plot correlations among these four factors. Here is the outcome.



It is clear that the correlations among factors are not severe. After that, we visualize their relationships. Here is the outcome.



You can see that some variables contributed little to our factors. At last, we got the recommendation of factors for a simple structure. Here is the result.



It is easy to find out that four factors are an appropriate choice from the graph above.

APPENDIX

Table 1: results for contributions and communality

	PC1	PC2	PC3	PC4	rowSums.bank.2.	PC1	PC2	PC3	PC4
bank$age	-0.00191648	0.20455664	-0.71171468	0.1211409 3	0.563059202	0.033857695	0.017038934	-0.717005188	-0.218004804
jobblue-collar	-0.14940844	-0.42609944	-0.12454290 9	0.126960374	0.235513491	-0.055953171	-0.278669488	-0.144420746	0.365880716
jobentrepreneur	-0.02064446	0.04105512 8	-0.06553942 5	0.078658761	0.012594334	-0.021267634	0.056472691	-0.093724137	0.012986249
jobhousemaid	-0.01652184 8	0.09386629 2	-0.14251582 2	-0.00389546 2	0.029409786	-0.018530092	0.020076729	-0.138362543	-0.097566615
jobmanagement	0.15392638 6	0.53763815	0.27522396 3	0.42622006 2	0.570159883	0.021815585	0.750326887	0.076157909	-0.029891463
jobretired	0.0280641	0.14019784 1	-0.46164829 5	-0.05739995 4	0.236856931	0.049878819	-0.064833796	-0.413880859	-0.242628256
jobself-employed	-0.02338202 9	0.05857846 9	-0.00336546 6	0.067937554	0.008604994	-0.033529559	0.079248868	-0.033717088	0.007971043

jobservices	-0.09015814949	-0.26112161642	0.03319935353	-0.19509117777	0.115475768	-0.04297730202	-0.31188068079	0.11188838889	0.06196896843
jobstudent	0.09134555252	0.01000711919	0.23879546565	-0.19039457	0.101717518	0.06365672727	-0.03032911414	0.29698365252	-0.09244563333
jobtechnician	0.01478426565	-0.03062750303	0.11910935555	-0.29896187171	0.104721857	0.00911937878	-0.17414470404	0.22193858593	-0.15828953636
jobunemployed	0.01498390808	0.01258194949	-0.01209572929	-0.07151689696	0.005643796	0.01393803	-0.03737401616	0.01510072828	-0.06184398383
jobunknown	0.01299964	0.08901893	-0.10276275959	-0.00589187777	0.018688175	0.00711038787	0.03158604646	-0.09804246	-0.08959696
maritalmarried	-0.11880074444	-0.04756795151	-0.69137375959	0.30200164	0.585578991	-0.03732044646	-0.05888972626	-0.75609971	0.09503370505
maritalsingle	0.14089544	0.04341312929	0.74870647878	-0.31457969191	0.681257997	0.05380643232	0.06798327	0.81586157676	-0.09006125151
educationsecondary	-0.13298801919	-0.57457485959	-0.10648949323	-0.52894152323	0.638941229	-0.01158071515	-0.78967924545	0.12155849393	0.02091265757
educationtertiary	0.20388123535	0.64942835757	0.35847652626	0.41508237171	0.764123544	0.04167352792	0.85362970909	0.15373282	-0.10034637575
educationunknown	0.01152423737	0.03028029595	-0.09037528153	0.08517653	0.016472437	0.01469182	0.05124312411	-0.11565271939	0.01597433939

default	-0.054147864	-0.026613592	0.039063572	-0.058069009	0.008538247	-0.05185097	-0.053149409	0.054521336	-0.007231051
bank$balance	0.084659968	0.157666292	-0.068452626	0.134826177	0.05488983	0.06042848	0.190255861	-0.116021026	-0.039749941
housing	-0.045625958	-0.537813721	0.181061912	0.281711727	0.403470239	0.033567176	-0.155100486	0.09876224	0.607069472
loan	-0.091438281	-0.055844387	-0.064837245	-0.141947318	0.035832464	-0.071825166	-0.162409036	-0.012367001	-0.064373692
contacttelephone	0.096927643	0.113464189	-0.266880576	-0.195049551	0.13153866	0.102575672	-0.103824417	-0.176113121	-0.28146323
contactunknown	-0.47923236	-0.384819541	0.127704324	0.481696903	0.626090035	-0.413728976	-0.007744789	-0.069797447	0.670810483
bank$day	-0.069910791	0.126000129	-0.00341248	-0.245105994	0.080852145	-0.089866796	-0.079027016	0.071151265	-0.247928078
monthaug	-0.030643426	0.426857373	-0.031678736	-0.183581093	0.217851796	-0.103789333	0.169330389	0.005248519	-0.422349669
monthdec	0.139243667	0.018828496	-0.013715488	-0.020332757	0.020344847	0.134214603	0.019315622	0.004987241	-0.043969551
monthfeb	0.165714331	0.039137438	0.006343289	-0.051579114	0.031693621	0.154455694	0.023869222	0.03568819	-0.077418814

monthjan	0.1638203 84	0.0541097 38	-0.0186693 97	-0.1596687 68	0.0556 07644	0.1529634 83	-0.0414022 4	0.0505114 97	-0.1671653 67
monthjul	-0.1654318 09	0.1596998 44	-0.1346797 12	-0.4024566 49	0.2329 81703	-0.1750917 05	-0.2079503 51	-0.0036374 13	-0.3988333 22
monthjun	-0.2396356 15	-0.0119332 19	-0.0012675 78	0.3175414 85	0.1584 01831	-0.2334668 05	0.1526732 94	-0.1354020 69	0.2495039 62
monthmar	0.0766214 37	0.0820653 99	-0.0694397 59	-0.0332262 53	0.0185 31438	0.0672658 85	0.0293680 23	-0.0515039 32	-0.1024285 28
monthmay	-0.0999723 67	-0.5831932 01	0.2070101 06	0.3633597 07	0.5249 92245	-0.0143462 61	-0.1368485 18	0.0917897 16	0.7054314 71
monthnov	0.1495082 52	0.1252470 52	-0.0510803 7	-0.0071444 53	0.0406 99789	0.1286182 68	0.0933520 63	-0.0408535 22	-0.1173606 08
monthoct	0.1462816 06	0.0832567 55	-0.1117229 64	-0.0233326 86	0.0413 5643	0.1394852 29	0.0358548 82	-0.0885046 78	-0.1130559 63
monthsep	0.1448819 61	0.0411573 04	0.0196054 77	0.0015510 69	0.0230 71487	0.1320978 1	0.0592337 95	0.0268367 33	-0.0373202 71
duration	0.0330461 9	-0.0509073 13	0.0128353 83	-0.0151759 83	0.0040 78663	0.0403502 44	-0.0362243 73	0.0236428 15	0.0240693 29
campaign	-0.1660995 72	0.1380362 06	0.0023674 12	-0.0929680 55	0.0552 91726	-0.1874190 16	0.0114533 72	0.0125221 6	-0.1409888 44

pdays	0.809222976	-0.28703815 5	-0.05859721 4	0.08644231 4	0.748138634	0.84926885 1	-0.03050187 1	0.00168454 2	0.16108336 6
previous	0.747870597	-0.20311384 1	-0.05979857 2	0.05545176	0.607216429	0.77422472 5	-0.00163823 2	0.00090659 9	0.08825530 3
poutcomeother	0.521799087	-0.16419049 8	-0.00176715 7	0.04855649 3	0.301593662	0.54011047 4	0.00070983 5	0.03559277 3	0.09277386 1
poutcomesuccess	0.393449128	-0.00599849	-0.11639 01	-0.03476695 4	0.169593595	0.39798094	0.00527479 1	-0.06192229 5	-0.08568856
poutcomeunknown	-0.901854867	0.23228001	0.09164203 8	-0.05814326 4	0.879075148	-0.93338613 2	0.00417865 8	0.01469693 7	-0.08736140 8